Comparison of Neural Networks for Prediction of Sleep Apnea

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Abstract: Sleep apnea (SA) is the most important and common component of sleep disorders which has several short term and long term side effects on health. There are several studies on automated SA detection but not too much works have been done on SA prediction. This paper discusses the application of artificial neural networks (ANNs) to predict sleep apnea. Three types of neural networks were investigated: Elman, cascade-forward and feed-forward back propagation. We assessed the performance of the models using the Receiver Operating Characteristic (ROC) curve, particularly the area under the ROC curves (AUC), and statistically compare the cross validated estimate of the AUC of different models. Based on the obtained results, generally cascade-forward model results are better with average of AUC around 80%.

1 INTRODUCTION

Sleep Apnea (SA) is one of the most common types of sleep disorders with around 3% prevalence in industrialized countries (Young, Palta et al. 1993). SA is characterized by a repeated and temporary cessation or reduction of breathing during sleep (Guilleminault et al., 1978). Clinically, apnea is defined as the total or near-total absence of airflow. This reduction becomes significant once the decline of the breathing signal amplitude is at least around 75% with respect to the normal respiration and occurs for a period of 10 seconds or longer. A hypopnea is an event of less intensity; it is defined as a reduction in baseline signal amplitude around 30–50%, also lasting 10 seconds in adults (Flemons et al., 1999). Sleep apnea also can be categorized to three types as; obstructive, central and mixed. The SA has several short term and long term side effects (Chokroverty et al., 2009). Short-term effects lead to impaired attention and concentration, reduce quality of life, increased rates of absenteeism with reduced productivity, and increased the possibility of accidents at work, home or on the road. Long-term consequences of sleep deprivation include increased morbidity and mortality from increasing automobile accidents, coronary artery disease, heart failure, high blood pressure, obesity, type 2 diabetes mellitus, stroke and memory impairment as well as depression. Long-term consequences, however, remain open (Chokroverty, 2010).

Unfortunately, as many patients are asymptomatic, sleep apnea may go undiagnosed for years (Kryger et al., 1996); (Ball et al., 1997). Usually it is patients' spouses, roommates, or family members who report the apnea periods alternating with arousals and accompanied by loud snoring (Stradling and Crosby 1990; Hoffstein 2000). Symptomatic patients with SA are usually assessed by sleep medicine Specialists and diagnosed through an overnight sleep study in a sleep clinic. SA is diagnosed by a manual analysis of a polysomnographic record, an integrated device comprising of the EEG, EMG, EOG, ECG, and oxygen saturation (SPO2) (Penzel et al., 2002). The polysomnography also contains records of airflow through the mouth and nose, along with the thoracic and abdominal effort signals (Kryger, 1992), and the position of the body during sleep.

The conventional scoring of the polysomnographic recording is laboured intensive and time-consuming (Kirby et al., 1999); (Sharma et al., 2004). Therefore, many efforts have been done to develop systems that score the records automatically (Cabrero-(Canosa et al., 2003); (de Chazal et al., 2003); (Cabrero-Canosa et al., 2004). For this reason several automated algorithms are used in this area such as; fuzzy rule-based system (Maali and Al-Jumaily, 2011), genetic SVM (Maali and Al-Jumaily, 2011) and PSO-SVM (Yashar and Adel, 2012) which have been proposed in our previous works.

As mentioned, there are several works on applications of predicting in different areas, but there are

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few studies in sleep apnea prediction. One of the earliest work was published by Dagum and Galper in 1995 (Dagum and Galper, 1995). This paper developed a time series prediction by using belief networks models and then this algorithm used in sleep apnea. This paper used a multivariate data set contains 34000 recordings, sampled at 2 Hz, of heart rate (HR), chest volume (CV), blood oxygen concentration (SaO_2), and sleep state from the time series competition of the Santa Fe Institute in 1991. Based on this study, prediction with the CV signal has more bias than HR and SaO2, because of rapid and erratic oscillations of the CV series.

Another pioneer work in sleep apnea prediction, we can can be found in Bock and Gough paper in 1998 . This study use 4.75 hz of heart rate, respiration force, and blood oxygen saturation (SaO_2) collected from a chronic apnea patient. They use simple recurrent networks (SRN) proposed by Elman (Elman, 1991). Each of three time series variables (heart rate, breathing, and blood oxygenation) were used as inputs for network training and testing operations. Each variable was introduced to a unique network node at the input layer; this network had 18 nodes in the hidden layer. «

One of the newest paper in this area is the work of Waxaman, Graupe and Carley in 2010 (Waxman et al.,). They predicted apnea 30 to 120 seconds in advance. They use Large Memory Storage And Retrieval (LAMSTAR) neural network (Graupe and Kordylewski, 1998). LAMSTAR is a supervised neural network that can process large amount of data and also provide detailed information about its decision making process. Input signals for this algorithm are EEG, heart rate variability (HRV), nasal pressure, oronasal temperature, submental EMG, and electrooculography (EOG). It must be noted that LAMSTAR has this ability to determine most important input (signal) in predicting process. In preprocessing phase, data that segmented of 30, 60, 90 and 120 seconds was normalized. They trained separate LAMSTAR for each 30, 60, 90 and 120 seconds segment. Results show that best prediction belongs to next 30 seconds and they obtained lower performance for longer lead time, however, most of predictions up to 60 seconds in the future is correct. Also, prediction of non-REM (NREM) events is better than REM events, generally. For example, for apnea prediction using 30-second segments and a 30-second lead time during NREM sleep, the sensitivity was 80.6 ± 6 5.6%, the specificity was 72.78 ± 66.6%, the positive predictive values (PPV) was 75.16 ± 3.6%, and the negative predictive values (NPV) was 79.4 ± 6 3.6%. REM apnea prediction demonstrated a sensitivity of 69.36 ± 10.5%, a specificity of 67.46 ± 10.9%, a PPV of 67.4 6 ± 5.6%, and an NPV of 68.8 ± 6 5.8%. Analyses also showed that the most important signal for the predicting apnea into the next second is submental EMG, and RMS value of the first wavelet level is the most important feature. But, for the 60 seconds prediction, nasal pressure is most important signal.

This paper discusses the development of supervised artificial neural networks, Elman, cascade-forward and feed-forward back propagation to predict sleep apnea. In the rest of this paper, the three NNs are introduced. Then the issues related to network design and training, especially how to avoid over fitting, are addressed. The use of AUC as performance measure of the models, and the statistical comparison of the overall performance of the models by means of cross-validation, are outlined. The results and conclusions are presented at the end of the paper.

2 PRELIMINARIES

2.1 Elman Neural Networks

The Elman neural network is one kind of globally feed-forward locally recurrent network model proposed by Elman (Li et al., 2009). It occupies a set of context nodes to store the internal states. Thus, it has certain dynamic characteristics over static neural networks, such as the Back-Propagation (BP) neural network and radial-basis function networks. The structure of an Elman neural network is illustrated in Figure 1.

It is easy to observe that the Elman network consists of four layers: input layer, hidden layer, context layer, and output layer. There are adjustable weights connecting every two adjacent layers. Generally, the Elman neural network can be considered as a special type of feed-forward neural network with additional memory neurons and local feedback. The distinct ‘local connections’ of context nodes in the Elman neural network make its output sensitive not only to the current input data, but also to historical input data, which is useful in time series prediction. The training algorithm for the Elman neural network is similar to the back-propagation learning algorithm, as both based on the gradient descent principle. However, the role that the context weights as well as initial context node outputs play in the error back-propagation procedure must be taken into consideration in the derivation of this learning algorithm. Due to its dynamical properties, the Elman neural network has found numerous applications in such areas as time series prediction, system identification and adaptive control (Gao and Ovaska, 2002).

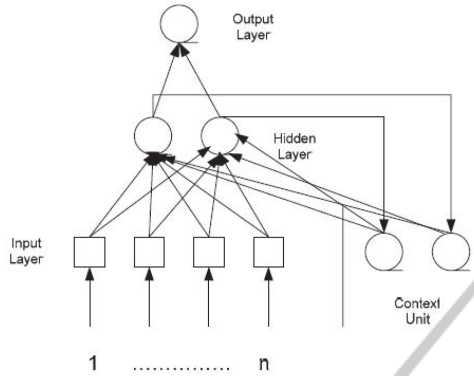

Figure 1: Structure of an Elman neural network model.

2.2 Cascade-forward Neural Network Models

Cascade-forward models are similar to feed-forward networks, but include a weight connection from the input to each layer and from each layer to the successive layers. While two-layer feed-forward networks can potentially learn virtually any input-output relationship, feed-forward networks with more layers might learn complex relationships more quickly. For example, a three layer network has connections from layer 1 to layer 2, layer 2 to layer 3, and layer 1 to layer 3. The three-layer network also has connections from the input to all three layers. The additional connections might improve the speed at which the network learns the desired relationship. Cascade-forward artificial intelligence model is similar to feed-forward back propagation neural network in using the back propagation algorithm for weights updating, but the main symptom of this network is that each layer of neurons related to all previous layer of neurons. This network is a Feed-Forward network with more than one hidden layer. Multiple layers of neurons with nonlinear transfer functions allow the network to learn more complex nonlinear relationships between input and output vectors (Abdennour, 2006).

3 PROPOSED APPROACH

In this paper three input signals as; airflow, abdominal and thoracic movement signals are used as had been found in our previous work as the most important signals for SA studies (Maali and Al-Jumaily, 2012). In the present work data collected from 5 patients which events of them are annotated by an expert were collected in the concord hospital in Sydney. We extracted data segments of 30, 60, 90, and 120 seconds. Also, Different lead times as 30, 60, 90 and 120 seconds are investigated in this paper. Also, AUC is considered as performance measure in this paper.

3.1 Feature Generation

Each signal from each segment was normalized by dividing by its mean value. A discrete wavelet transform was then applied. For each windows a variety of features were extracted from the nasal airflow, abdominal and thoracic movement signals. Features are generated from coefficients of wavelet packet and the original signals. Daubechies wavelet packet of order 4 and 7 levels is used and different statistical measures are generated from the coefficients and original signal. These features represent the inputs of the NNs algorithm. Full list of proposed features are included in the Table 1.

Table 1: List of statistical features, x is coefficients of the wavelet.

log(mean(x^2))	kurtosis(x^2)	geomean(abs(x))
std(x^2)	var(x^2)	mad(x)
skewness(x^2)	mean(abs(x))	mean(x^2)
skewness(x)	kurtosis(x)	var(x)
geomean(x^2)	mad(x^2)	std(x)

More details about these statistical measures are presented in the Appendix

3.2 Early Stopping

Usually standard neural network architectures such as the fully connected multi-layer perceptron almost always are prone to overfitting. While the network seems to get better and better (the error on the training set decreases), at some point during training it actually begins to get worse again, (the error on unseen examples increases).

There are basically two ways to fight overfitting: reducing the number of dimensions of the parameter space or reducing the effective size of each dimension. The corresponding NN techniques for reducing the size of each parameter dimension are regularization such as weight decay or early stopping (Prechelt, 1998). Early stopping is widely used because it is simple to understand and implement and has been reported to be superior to regularization methods in many cases. This method can be used either interactively, i.e. based on human judgment, or automatically, i.e. based on some formal stopping criterion. In this paper automatic stopping criteria is used based on the increases of validation error.

4 RESULTS

The results for prediction of apnea in the immediately following segment as the segment duration are varied between 30, 60, 90 and 120 seconds are computes for each of three NNs. For each experiments10 validation is performed and average and standard deviation of these results are shown in table 2, 3 and 4. ANOVA test on these data shows that the average of AUC of these segmentations are significantly different and performing pair t-test shows that performances are generally better for 30-seconds segment, and as the segment duration is increased, the performance is decreased. Also, increase of the lead time results in increasing of the performances.

Table 2: AUC of apnea prediction by Cascade-forward model.

	Lead Time			
	30	60	90	120
30	71.05 ± 2.42	75.29 ± 3.79	78.15 ± 5.75	82.22 ± 3.93
60	67.71 ± 1.93	72.55 ± 7.29	77.68 ± 5.92	79.66 ± 5.79
90	66.29 ± 4.43	71.85 ± 8.17	80.47 ± 4.54	81.05 ± 4.97
120	63.40 ± 1.54	73.44 ± 6.26	78.19 ± 7.72	77.52 ± 7.18

Table 3: AUC of apnea prediction by feed-forward model.

	Lead Time			
	30	60	90	120
30	68.12 ± 2.43	74.88 ± 5.77	73.61 ± 5.76	82.31 ± 7.19
60	65.56 ± 2.72	72.90 ± 7.48	71.71 ± 6.23	80.45 ± 6.50
90	65.95 ± 4.43	69.31 ± 5.20	73.08 ± 8.67	72.90 ± 7.53
120	61.12 ± 1.47	67.12 ± 7.83	76.39 ± 8.38	79.72 ± 6.52

Table 4: AUC of apnea prediction by Elman model.

	Lead Time			
	30	60	90	120
30	69.32 ± 2.24	74.88 ± 5.77	73.61 ± 5.76	78.31 ± 7.19
60	67.59 ± 2.53	77.64 ± 7.34	78.49 ± 4.81	79.16 ± 6.43
90	64.87 ± 1.68	77.02 ± 5.90	77.62 ± 6.85	79.99 ± 5.94
120	65.57 ± 2.28	72.88 ± 7.14	76.46 ± 8.31	79.83 ± 5.19

Also, ANOVA test shows that performance of these models are not same, and in general cascade model results in better prediction, but not for all of the experiments, this shows that each model can predict some type of samples better than other models. Therefore using ensemble of neural networks maybe helpful and should be considered (Li et al., 2009).

5 CONCLUSIONS

In this study, we present the first step of an ongoing investigation into the prediction of individual events of sleep apnea with different artificial neural networks. Experimental results of Elman, cascade-forward and feed-forward back propagation neural networks shows that, generally cascade-forward NN can predict the sleep apnea events better, but this advantage is not for all samples and investigation on ensemble of these NNs is subject to future works. Also, this study shows that increasing the lead time can improve the performances, in the most cases.

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APPENDIX

Mean, variance (VAR) and standard deviation (STD) are common and well known statistical tools, so other statistical features, in this study, are reviewed here.

Kurtosis: The kurtosis of a distribution is a measure of how outlier-prone a distribution is, and defined as follow

$$k = (E(x-\mu)^4)/\sigma^4$$

Geomean: Geomean is the geometric mean and computed as follow:

$$m = (\prod x)^{(1/n)}$$

Skewness: Skewness is a measure of the asymmetry of the data around the sample mean, and defined as follow

$$s = (E(x-\mu)^3)/\sigma^3$$

Mad: mad is mean absolute deviation of the sample as, $mean(|(x - mean(x))|)$.